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STUDYING AND FORECASTING OF THE PHOSPHATES POLLUTION DYNAMICS IN WATERSHEDS AND ANTROPOGENIC WATER MANAGEMENT LANDSCAPE DYNAMICS: APPLICATION TO THE SMALL CARPATHIANS RIVERS' WATERSHEDS

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Abstract. The paper concerns the results of the quantitative study of dynamics for phosphates concentrations in the Small Carpathians rivers watersheds in Earthen Slovakia by using methods of nonlinear analysis and forecasting, chaos theory and dynamical systems. The conclusions can be viewed from the perspective of carrying out new algorithms for analysis and forecasting of the dynamics and evolution of anthropogenic water management landscape. Chaotic behaviour of the phosphates concentration time series in the watersheds of the Small Carpathians is studied. It is shown that low-D chaos exists in the time series under investigation.

Key words: dynamics, studying, forecasting, phosphates concentrations, the Small Carpathians rivers watersheds, chaos theory methods.

Introduction

In modern theory of the hydro-ecological systems, water resources and environmental protection, the problem of quantitative treating of pollution dynamics is also one of the most important and fundamental problems, in particular, in applied ecology and urban ecology [1–18]. Let us remind [1–9] that most of the models are currently used to assess (as well as forecast) the state of the environment pollution by the deterministic models or their simplification, based on simple statistical regressions. The success of these models, however, is limited by their inability to describe the nonlinear characteristics of the pollutant concentration behaviour and lack of understanding of the involved physical and chemical processes. Especially serious problem occurred during the study of dynamics of the hydro-ecological systems. Although the use of chaos theory methods establishes certain fundamental limitation on the long-term predictions, however, as it has been shown in a series of our papers (see [1–22]), these methods can be successfully applied to a short-or medium-term forecasting.

These studies show that chaos theory methodology can be applied and a short-range forecast by the non-linear prediction method can be satisfactory. It opens very attractive perspectives for the use of the same methods in studying dynamics of the pollution of other hydro-and ecological systems. Earlier the pollutions variations dynamics of nitrates concentration in the river water reservoir in Earthen Slovakia was studied by using a chaos theory [9]. Here a non-linear behaviour of the phosphates concentration in time series in the watersheds of the Small Carpathians is studied. All calculations are performed with using "Geomath" & "Quantum Chaos" PC codes [9, 16, 17, 23–42].

Method of testing of chaos in time series

As the initial data we use the results of empirical observations made on six watersheds (Fig. 1.) in the region of the Small Carpathians, carried out by co-workers of the Institute of Hydrology of the Slovak Academy of Sciences [2]. Fig. 2 shows temporal changes in the concentrations of phosphates in the catchment areas. In Fig. 3 we list the Fourier spectrum of the concentration of phosphates in the water catchment of Vydrica (C-Most) for the period of 1991–1993. The X-axis - frequency, the axis Y – energy.

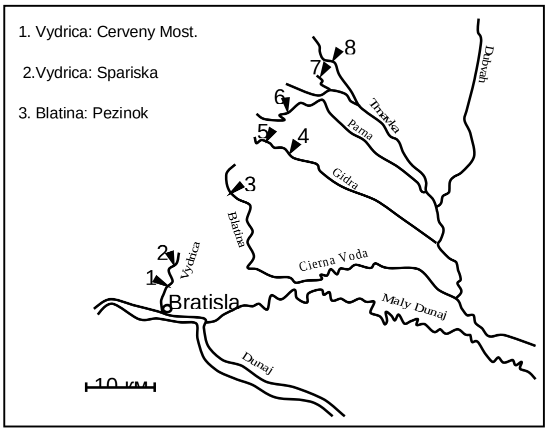

Fig. 1. Observation sites in the Small Carpathians [2]

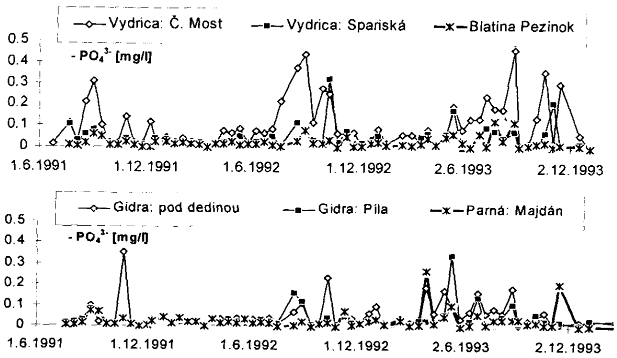

Fig. 2. Temporal changes in the concentrations of phosphates in some water catchments of the Small Carpathians (Slovakia) [2]

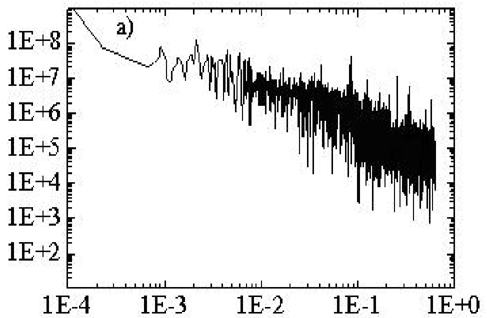

Fig. 3. The Fourier spectrum of the concentration of phosphates in the water catchment area of Ondava (Stropkov) for the period of 1.6.1991–2.12.1993

The Fourier spectrum looks the same as in the case of a random process, so there is the possibility of using methods of chaos theory.

Let us consider scalar measurements: $s(n)=s(t_0+ + n\Delta t) = s(n)$, where t_0 is start time, Δt – a time step, and n – a number of measurements. The key task is to reconstruct phase space using the information contained in $s(n)$. Such reconstruction results in a set of d-dimensional $\mathbf{y}(n)$-vectors for each scalar measurement. The main idea is the direct use of variable lags $s(n+\tau)$, where τ is some integer to be defined, which determines the coordinate system where a structure of orbits in phase space is restored. Using a set of time lags to get a vector in d dimensions,$y(n)=[s(n),s(n + \tau),s(n + 2\tau),..,s(n +(d–1)\tau)]$, the required coordinates are provided. In a nonlinear system, $s(n + j\tau)$ are some unknown nonlinear combination of the actual physical variables. The dimension d is the embedding dimension, d_E.

The choice of a proper time lag is important for subsequent reconstruction of phase space. If τ is too small, then the coordinates $s(n + j\tau)$, $s(n +(j +1)\tau)$ are so close to each other in numerical value that they cannot be distinguished from each other. If τ is too large, then $s(n+j\tau)$, $s(n+(j+1)\tau)$ are completely independent of each other in a statistical sense. If τ is too small or too large, then the correlation dimension of attractor can be under-or overestimated. One needs to choose some intermediate position between the above listed cases. The first approach is to compute the linear autocorrelation function $C_L(\delta)$ and determine such time lag in which $C_L(\delta)$ is the fastest when passing through 0. This gives a good hint of choice for τ at which $s(n+j\tau)$ and $s(n+(j +1)\tau)$ are linearly independent. It's better to use the approach of nonlinear concept of independence, e.g. of average mutual information. The average mutual information I of two measurements a_i and b_k is symmetric and non-negative, and equals to 0 if only the systems are independent. The average mutual information between any values a_i from system A and b_k from B is the average over all possible measurements of $I_{AB}(a_i, b_k)$. In ref. [3] it is suggested to choose such value of τ where the first minimum of $I(\tau)$ occurs.

The goal of the embedding dimension determination is to reconstruct Euclidean space R^d large enough so that the set of points d_A can be unfolded without ambiguity. The embedding dimension, d_E, must be greater, or at least equal to the dimension of attractor, d_A, i.e. $d_E > d_A$. In other words, we can choose a fortiori large dimension d_E, e.g. 10 or 15. The correlation integral analysis is one of the widely used techniques to investigate chaos in time series. The analysis uses the correlation integral, $C(r)$, to distinguish between chaotic and stochastic systems. According to [4], integral $C(r)$ is calculated based on the algorithm. If the time series is characterized by an attractor, the correlation integral $C(r)$ is related to the radius r as

$$d = \lim_{\substack{r\to 0\\ N\to\infty}} \frac{\log C(r)}{\log r},$$

where d is a correlation exponent. If the correlation exponent attains saturation with an increase in the embedding dimension, then the system is generally considered to exhibit chaotic dynamics (see refs. [4, 16, 17]).

Fig. 4 lists the dependence of the correlation dimension (axis Y) on the embedding dimension (axis X) for the concentration of phosphates in the watershed of Ondava (Stropkov) for the period of 1991–1993. There is a corresponding curve, the analysis of which shows that saturation value for d_2 concentrations in the watershed of Vydrica (C.Mist) for the studied period of 1991–1993 amounts to 6.3 and was achieved by embedding dimension *ds*, at 18. The same result is obtained on the basis of false nearest neighboring points (Fig. 4). The dimension of the attractor in this case was defined as the embedding dimension, in which the number of false nearest neighboring points was less than 3 %.

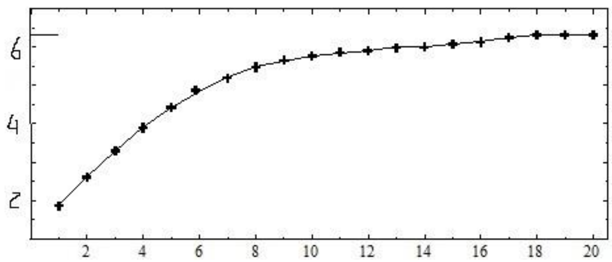

Fig. 4. The dependence of the correlation dimension (axis Y) on the embedding dimension (axis X) for he concentration of phosphates in the watershed of Vydrica (C.Miost) for the studied period of 1991–1993

It is known that the limited predictability of chaos is quantified by local and global Lyapunov exponents. The Lyapunov exponents are related to the eigenvalues of the linearized dynamics across the attractor. Large positive values determine some average prediction limit. Since the Lyapunov exponents are defined as asymptotic average rates, they are independent of the initial conditions, and hence the choice of trajectory, and they do comprise an invariant measure of the attractor. An estimate of this measure is a sum of positive Lyapunov exponents. The estimate of the attractor dimension is provided by the conjecture d_L and the Lyapunov exponents are taken in descending order. To compute them, method of linear fitted maps [1, 2] is used. The sum of positive Lyapunov exponents determines the Kolmogorov entropy, which is inversely proportional to the limit of predictability ($Pr_{\max}$).

Results and conclussions

In Table 1 we list the values of the time delay (τ), depending on the different values of the autocorrelation function (C_L) and the first minimum of mutual information ($I_{\min1}$) for the concentration of phosphates in the watersheds of the Small Carpathians.

Table 1

The values of time delay (t), depending on different values of autocorrelation function (C_L) and the first min of mutual information ($I_{\min1}$) for phosphates concentration in the studied watersheds

River (Site)	C_L = 0	C_L = 0,1	C_L =0,5	$I_{\min1}$
Vydrica (C.Most)	–	288	57	24
Vydrica (Spariska)	–	289	55	22
Blatina (Pezinok)	–	316	66	21
Gidra (Main)	–	274	53	19
Gidra (Pila)	–	267	52	22
Pama (Majdan)	–	314	63	20

Table 2 summarizes the results of the numerical reconstruction of the attractors, as well as average limit of predictability ($Pr_{\max}$) and Gottwald-Melbourne parameter K [5] for the phosphates concentrations in the watersheds of studied region.

Table 2

Time lag (t), correlation dimension (d_2), embedding dimension (d_E), the Kaplan-Yorke dimension (d_L), average limit of predictability ($Pr_{\max}$) and parameter *K* for the phosphates concentrations in the watersheds of the Small Carpathians

River (Site)	τ	d_2	d_E	d_L	$Pr_{\max}$	K
Vydrica (C.Most)	21	6,3	7	5,1	11	0,7
Vydrica (Spariska)	20	6,7	7	5,8	12	0,6
Blatina (Pezinok)	20	5,9	6	6,1	13	0,6
Gidra (Main)	17	6,1	7	6,8	14	0,7
Gidra (Pila)	18	6,8	7	6,4	11	0,7
Pama Majdan)	19	5,2	6	5,8	11	0,6

As it was indicated, the sum of positive Lyapunov exponents λ_i determines the Kolmogorov entropy, which is inversely proportional to the limit of predictability ($Pr_{\max}$). Let us remind that since the conversion rate of the sphere into an ellipsoid along different axes is determined by the λ_i, it is clear that the smaller the amount of positive dimensions, the more stable is a dynamic system. Consequently, it increases its predictability.

On the other hand, the conclusions can be viewed from the perspective of new algorithms for the analysis and forecasting of the dynamics and evolution of anthropogenic water management landscape. Therefore in this paper we present the results of studying the dynamics of variations of phosphates concentrations in the rivers water reservoirs in Earthen Slovakia) systems in the definite region by using non-linear prediction approaches and chaos theory methods. Chaotic behaviour in the phosphates concentration time series in a number of the the watersheds of the Small Carpathians (Slovakia). We have shown that low—middle-dimensional chaos elements exist in the time series under investigation and quite sufficient predictability can be obtained in the forecasting of the pollution concentrations dynamics.

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